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A MODEL-BASED APPROACH FOR THE LONG TERM PLANNING OF DISTRIBUTED ENERGY SYSTEMS IN THE ENERGY TRANSITION

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ABSTRACT

Energy system models need to adapt to better represent the new challenges brought by a changing scenario regarding technologies development and policy making. The mixed integer linear programming based approach proposed in this study wishes to handle the impacts of these changes on potential investments in distributed energy systems, whose design is to be determined for a time horizon lasting several years with parameters that might change even substantially in such timespan. In order to test the approach, a scenario representing a residential district with high penetration of electricity production from non controllable sources (photovoltaic panels) is used as a test case.

The investment decision under examination is when to possibly deploy a battery system to deal with the production surplus generated during the day by the mismatch in production and demand. While electricity can be fed into the grid by taking advantage of a feed-in tariff scheme, this could not be the most economically favorable approach due to the dropping costs of the Lithium-ion battery systems in the near future.

Results show that for the case study under analysis investing into batteries appears not convenient in terms of overall costs, although the best alternative solution provided with storage systems is only slightly more expensive.

Keywords: energy transition, distributed energy systems, energy systems design, energy modeling

NONMENCLATURE

1. INTRODUCTION

The energy transition entails significant and potentially disruptive changes to the current energy generation systems and distribution infrastructures, with such changes happening both on technologies and policies being adopted. Regarding the first aspect, technologies such as solar photovoltaic and Lithium-ion batteries are undergoing significant drops in capital costs [1,2]. On the policies side, many governments are already committing to a profound decarbonisation of our society and in some cases establishing new new regulations with this aim [3]. Finally a third trend lies in the decentralization of the energy production system, with smaller and more numerous energy conversion and storage systems placed close to final consumers, contrary to the large centralized production and distribution infrastructure that characterized energy fruition so far. The reasons for decentralization are multiple: from an increased reliability of the system to a design choice which is more tailored to the specific needs of the particular user, and ultimately to an easier management of non controllable energy generation sources.

In this scenario designing an energy system becomes much more complex, due to the wide set of aspects that have to be taken into account: from the variety of technologies available to the external conditions such as availability of natural resources (solar radiation, wind etc.) and the access to energy markets which follow different tariff schemes [4]. All of these conditions might also change in time for the anticipated reasons: a technology could drop in cost due to technological advancement or economies of scale, or a new tax/incentive could intervene to change the convenience of certain resources in spite of others. To address these challenges, many modeling approaches have been proposed in the literature [5,6], each addressing more in detail one of the various aspects of distributed energy systems design [7].

The mixed integer linear programming (MILP) based approach proposed in this study wishes to handle the dynamism of the external conditions that affect the optimal design of a distributed energy system providing the needs of a grid connected urban district, meaning a context where electricity and natural gas can be bought from the traditional centralized distribution infrastructures, but also where distributed systems can be purchased and deployed locally to meet the needs of the users. In particular, the approach incorporates the long-term temporal dimension of the problem, determining the optimal design over a timespan of several years, which represents the planning horizon for the district under analysis. This is achieved by modeling two different timescales: a smaller one to represent the day to day workings of the systems in the district, where the dispatch decisions are made on an hourly basis; and secondly a multi-year one where the actual investment decisions are made.

To the best of the authors knowledge a similar approach has been only followed in [8] by integrating the EnergyPLAN simulation software [9] with an external optimization shell using a genetic algorithm to determine transition pathways for a national scale energy system. The solution approach proposed in this work is innovative both due to the implemented meataheuristic approach itself, and to the achievement of an optimal solution also on the operational phase, where the decision regarding the dispatch strategy of the energy systems are made for a district scale energy system.

This is validated by analyzing a scenario representing a realistic residential user with a high non controllable electricity generation source, where the decision under analysis regards the adoption of an electricity storage system to be made under different feed-in tariff schemes.

2. MILP AND SOLUTION ALGORITHM

In general terms the problem can be described as the design of a distributed energy system in which the demand of different energy vectors must be fulfilled by scheduling the operational activities of the installed technologies. Decisions are taken in order to minimize the total costs sustained to meet the energy demands of the district within a fixed time horizon by a single entity (such as for example a local municipality or energy community).

To solve this problem, the first idea was to expand the mathematical formulation presented in [10] by expanding the time horizon to a multi-year schedule but this would have led to an intractable MILP. The solution approach proposed in this paper relies on two phases designated to solve the problem in cyclical subsequent steps with a different time-scale and different purposes. This heuristic approach can overcome the intractability of the whole general formulation by relying on a two-phase approach that can be described as follows, with a graphical representation of the proposed two-phase algorithm is shown in Figure 1:

- **Phase 1:** a problem formulation M is used to solve the design and scheduling problem on the multi-year horizon and provides the set of technologies to install on each year.
- **Phase 2:** a problem fomulation M_h is iteratively solved on subsequent one week long time slices with hourly resolution until the multi-year horizon is (partially) covered, each time taking into account only the technologies that results installed within the time interval.

In the first phase a MILP formulation (M) operates the decisions of investment into technologies within a multi-year horizon in which boundary conditions may change and the lifecycle of systems is taken into account. Thus, the model uses binary variables to determine the choices regarding the purchase and installation of technologies within a particular year. Furthermore, additional binary variables are employed within constraints to ensure that a selected technology can be exploited only for a restricted timespan, that is coherent with the technical lifetime of the considered technology. Demand constraints are enforced by considering the annual aggregated demand for each energy vector: at each year, the total amount of each energy vector required by the district has to be satisfied by means of the internal output produced by the deployed technologies, the energy stored within installed storage systems and the possible supply provided by external suppliers (e.g. national grid). Moreover, the potential surplus of energy can be converted into revenue by feeding it into the external grid in the case of the electricity vector.

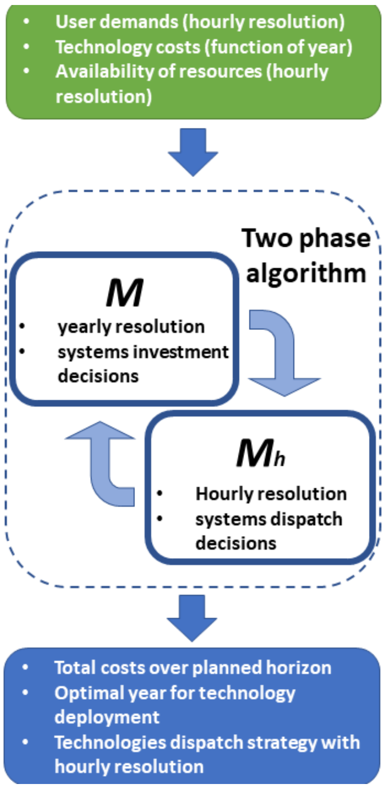

Figure 1 – Graphical representation of the algorithm

Continuous variables $q \in \mathbb{R}^+$ and $p \in \mathbb{R}^+$ are used to model the amount of input and output power of each conversion technology i. The output at each time step t of such technologies is assumed linear by imposing the following relation:

$$p(i,k,t) = \omega_i \times q(i,h,t)$$

where k and h indicate the output and input vectors of energy, respectively, and ω_i is the conversion efficiency of technology i. Moreover, the power generated by conversion technologies is constrained within maximum and minimum rated limits that, starting by the specifications of real systems, are set equal to annual aggregated values. For the case of renewables systems as the photovoltaic, the produced electric energy is considered linearly dependent by the efficiency of panels, the surface covered by the photovoltaic system and the aggregated exposition to solar radiation within each year. The specifications of the storage systems are modeled with the annual scaled storing capacity and a linear charging/discharging efficiency.

Finally, M aims at minimizing the total costs objective function that accounts for the investment for purchasing and installing technologies at a certain year, their annual maintenance costs, the total expenses and revenues respectively related to the purchasing and selling of energies from/to external suppliers, the potential price for storing energy. An optimal solution of M describes a set of technologies that compose the design of the energy district, along with their scheduling on the annual perspective. However, the coarse grained schedule depicted by the solution can be affected by approximation errors that derives by moving from the real hourly scale on which the technologies operates, to the aggregated yearly scale in which strategical decisions are performed.

Hence in the second phase, a second MILP (M_h) is exploited to optimize the scheduling of deployed technologies on a small subset of representative hours (hourly time horizon) of the year. In this way, the strategical decisions implemented on the annual horizon are linked with the schedule of operations defined by solutions built on the hourly horizon. Formulation M_h is based on a subset of constraints which compose M, that is the demand fulfilment inequalities and the constraints related to the operations and bounds of productive technologies and storage systems. The objective function minimizes the sum of the costs for external supplies and storing energy, minus the revenues for the amount of energy sold.

Each solution obtained by M_h can result (*i*) unfeasible, if the demand of an energy vector cannot be met by the current layout of the district and cannot be supplied by external sources; (*ii*) feasible, with specific values of energy produced, purchased, stored and sold. In case (*i*), constraints are added to M to enforce that technologies and storage systems within the energy district are able to satisfy the maximum unmet hourly demands of energy vectors. In case (*ii*), constraints are added to M in order to reduce the amount of energy supplied by external vendors. This is done by enforcing that, for the hour in which the purchased quantity of external supply reaches the maximum value, a percentage ϑ of the corresponding demand is satisfied by the operations of technologies and storage systems. In both (*i*) and (*ii*) constraints consider the hourly demand, the technical parameters of the systems scaled to hourly resolution and are indexed with the year in which the hour that defines the unfeasibility or the peak of external supply belongs to.

After that the definition of the hourly schedule is achieved for all the considered intervals of hours, a new overall solution is reached if no unfeasibility was detected. Its value is computed as the sum of the investment and maintenance costs of the solution of M plus the total expenses related to the schedule of operations given by solutions of M_h. The algorithm then updates ϑ by a small step and iterates, starting again with the first phase. The whole procedure ends after a fixed number of iterations or if $\vartheta > 1$. The solution with minimum overall cost is selected as the best one.

3. CASE STUDY AND RESULTS

3.1 Case Study

The proposed case study represents a residential district in the United States, whose demand is simulated by referring to a publicly available dataset containing the data regarding energy consumption and production by means of photovoltaic systems of 1000 households situated in Austin (Texas) [11] in 2013 with a high time resolution. The demand of a residential district has then been recreated by adding up the demands of 150 users and the same has been done for the production from the photovoltaic panels, in order to obtain the inputs for the model which are provided as a timeseries spanning a year with hourly resolution. The district is also considered to be connected to both an electricity and natural gas network distribution infrastructures, from which it can withdraw the respective commodities with a flat tariff scheme.

In order to reduce the size of the problem only a representative subset of the yearly data has been used. This has been achieved by means of a k-means clustering procedure [12], from which a subset of 6 weeks has been selected using the average weekly demands (for each energy commodity) and the average PV system electricity production. Three of the selected weeks (winter, mid-season and summer) are shown in Figures 2 to 5, where their solar radiation and their heating, cooling and electricity demands are respectively shown.

Other than the PV system, which size is given as an input to the simulation, two more conversion technologies are considered within the analyses: a natural gas boiler to meet the heating demand and an electric split system to meet the cooling demand.

Given the high electricity production achieved by means of the PV system, a surplus of production can occur and such surplus of electricity can either be fed into the local grid in exchange for a monetary compensation or be stored for consumption later in the day.

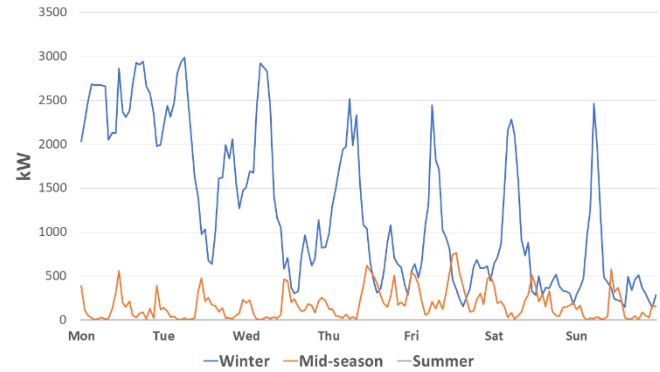

Figure 2 – weekly heating demand

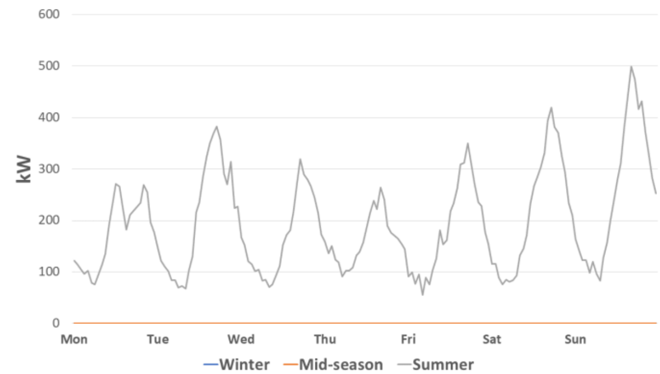

Figure 3 – weekly cooling demand

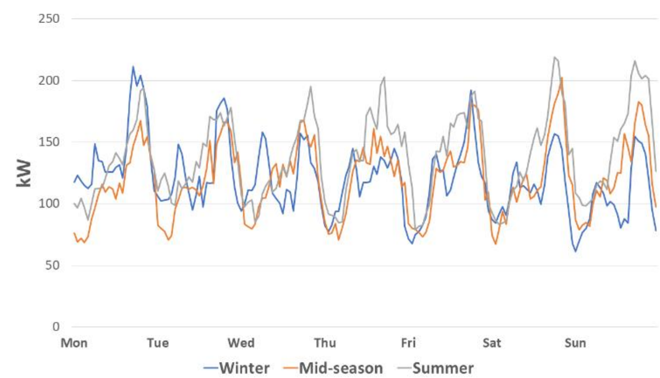

Figure 4 – weekly electricity demand

Therefore, what we wish to investigate with this model is the optimal year (if one) to adopt a battery energy storage system in order to deal with the surplus of electricity generation, given a decreasing purchase cost driven by the market. The lowering in capital costs is simulated by referring to [13], with the obtained projected costs shown in Figure 6. The adoption of batteries is studied under different feed-in tariff schemes, with the highest retribution value set as half of the electricity purchase cost, this with a series of scenarios C^*. Moreover the purchase of a battery is forced on the system through another set of scenarios C^B, this in order to both analyze the gap in terms of costs with the previous set, and test the validity of the dispatch strategy simulation.

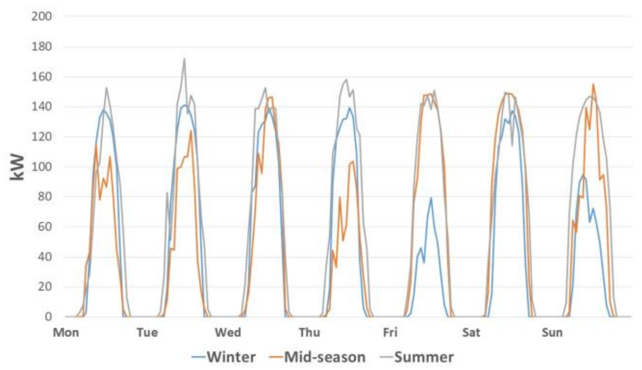

Figure 5 – production of the PV system already in place

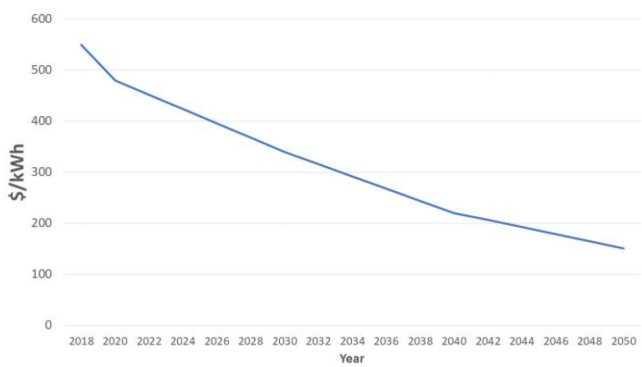

Figure 6 – Assumed costs of battery systems in the planning horizon

3.2 Results

The results obtained highlight that, in terms of the overall cost for the design and management of the energy district in the planning horizon of thirty years, the best solution has no battery installed for each considered feed-in tariff scheme. The electricity demand is met by means of the production of the photovoltaic panels and by purchasing from the national grid, with all of the surplus electricity sold to the grid to take advantage of the feed-in tariff. As expected the heating and cooling demand are met respectively by means of a boiler and an electric split system, which investment costs are renewed after their technical lifetime expires.

Table 1 shows the overall costs for the best solutions for C^* and C^B. Moreover, the percentage gap (between the battery and non battery scenarios solution) of the overall costs is reported *G*.

The overall system cost for the whole timespan considered (30 years) is 5744.64 k$ on average, with a slight decrease of 0.034% while moving from a feed-in tariff retribution value of 0.02 $/kWh to 0.04 $/kWh. On the other hand, the percentage gap *G* slightly increases from 0.69% to 0.71%. All the solutions provided by *M* show that the natural gas boiler and the electric split system are renewed after the nominal lifetime of twenty years, whereas C^B has batteries of 50 kWh bought in the first and twenty-first years of the horizon. For different values of FIT, the solution for C^B changes in the hourly schedule of the electrical energy. Comparing C^* and C^B, the gap results extremely limited to 0.70% on average, meaning that the adoption of a battery system is just slightly more expensive for the proposed test case.

FIT [$/kWh]	C^* [k$]	C^B[k$]	*G*
0.02	5745.61	5785.39	0.69
0.025	5745.12	5785.19	0.70
0.03	5744.64	5785.00	0.70
0.035	5744.15	5784.80	0.71
0.04	5743.67	5784.60	0.71
Average	5744.64	5785.00	0.70

Table 1 – Best solutions for different feed-in tariff (FIT) schemes

Even if the investment in batteries appears not balanced by the saving in terms of reduction of purchased electricity, practically speaking energy systems equipped with batteries are able to better absorb the uncertainty of the demand and a solution like the one C^B can still appear a reasonable choice. In Figure 7 the dispatch of the electricity vector (in a C^B scenario) for an example week is shown: it can be seen that surplus electricity is both stored and sold to the main grid.

For this particular test case (which is a realistic purely residential user) it can be concluded that the adoption of a battery system to manage the surplus of electricity from the non controllable PV panels is not convenient from an economical standpoint even considered the dropping system investment costs. The situation might change if more PV panels are deployed or if the feed-in tariff compensation reduces.

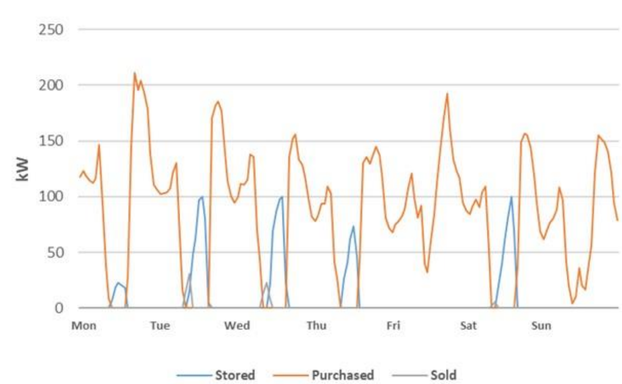

Figure 7 – Electricity dispatch over one week

The code was implemented in AMPL v.20180308 (MS VC++ 10.0, 64-bit) and experiments were performed on a Intel^r Core i7-7500U 2.90 GHz with 16Gb RAM. All the MILP were solved by IBM^r CPLEX^r 12.9.0.0. To solve all the MILPs for all the iterations, the solution algorithm required on average 51.40 seconds.

4. CONCLUSIONS

In this paper, a MILP based approach for the design of distributed energy systems is presented. User demands of multiple types of energy commodities are considered and investment choices are performed under parameters variation within a multi-year time horizon. The proposed algorithm has two phases in which different timescales are considered: the first phase defines the layout of the energy district by taking into account the changes of technological parameters during the planning horizon; in the second phase, an hourly resolution is used to represent the day-to-day functioning of the systems to meet users energy demands.

The case study analyzed in this paper represents a residential district with high renewable electricity generation. The adoption of battery system has been evaluated according to purchasing price variation that is supposed to decrease during time.

Results showed that investing into batteries appears not convenient in terms of overall costs for this case study, although the best alternative solution provided with storage systems was only slightly more expensive and can represent a robust alternative under the uncertainty of the demand in practice.

Future steps could further expand the modeling capabilities of realistic urban districts, by as example considering the spatial discretization in different groups of buildings or the stochastic nature of some of the cost and technical parameters considered in the analyses.

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